# GAN proposal part

Scientific data collection is expensive and time consuming. Generative adversarial network (GAN) [1] is a recent data generation framework that attracts great attentions and have seen significant progress [2]–[5]. GANs proposed to generative tasks through a minimax game between two competing networks, the generator and discriminator, and such a methodology have great success on computer vision datasets [6]. Recent development in GANs greatly improve the training stability and mode completeness of generated samples [7], [8], [2]. Another trend of research focus on improve the expressiveness of GANs, such as teaching GANs the ability to generate samples of a specific class [3], [9], improving GANs’ performance on image data [10], conditioning GANs’ generated samples on input images [4], [11], [5], [12]. Among these works on GANs, we found 4 areas that have great potential and are very promising to applying GANs to scientific data.

## Noise removal

Scientific data collection is usually limited by the physical constraints such as expensive instruments and possible effects on the sample. For example, collecting microscopy images of live creatures is commonly facing trade-offs between images quality, spatial resolution, imaging speed. Generative models [13] have been adopted to improve the microscopy image quality and shows very promising results [14]. Similar models based on GANs have also seen great potential on computer vision tasks, such as image style translation [4], [11].

## Data augmentation

GANs can also find great applications in augmenting existing data such as temporal interpolation. As high frequency imaging may be limited by the capability of equipment or cause possible damage to the sample that is prohibited in practice. Recent researches [4], [5], [11] in computer vision field that conditioning GANs’ generated samples on given images are very suitable for this kind of tasks.

## 3-D reconstruction

Another possible application of GANs on scientific data is 3-D reconstruction from 2-D or pseudo 3-D images. For example, for microscopy images, due to the limitation of equipment, a stack of images that representing a 3-D embryo usually suffer from image quality drop at many slice images in a stack. GANs have potentials to eliminate this problem by learning images of same embryos taken from different angles. Similar works including 3DGAN [15] that can generate 3D models from 2D images is of great interest for industrial engineering.

## Classification and Pattern Detection

Although there are a huge number of data available, scientific data are usually only suitable for unsupervised tasks as they lack labels for patterns of interest. However, classifiers [16]–[19] used in computer vision tasks usually require huge number of labeled data to train. Unlike computer vision dataset which anyone with common knowledge can help the labeling process, scientific data often requires human labor with strong domain knowledge to manually label the data. To solve this problem, we recently study the possibility of using GANs to learn features from unlabeled data and then transfer its learned features to Convolutional Networks to speed up further training. In this way, only a small labeled dataset is required for classification [21] or detection [20] tasks.

# ImageNet and famous classifiers

ImageNet[6] contains more than 14 million labeled images of over 20 thousand categories. It hosts the ImageNet Large Scale Visual Recognition Challenge (ILSVRC) annually.

Noticeable winner that using Convolutional Neural Networks (CNNs) with lowest top-5 errors:

2012: AlexNet[16] has top-5 error of 15.3% (improved from 25.7% of 2011 winner). It has 8 layers of total 60M parameters.

2014: GoogLeNet[17] and VGGNet[18] have top-5 error of 6.67% (improved from 14.8% of 2013 winner). GoogLeNet has 22 layers of 4M parameters and VGGNet has 16 layers of 140M parameters.

2015: ResNet[19] has top-5 error of 3.57%, which is beyond the ability of human expert who has 5.1% error rate. It has 3 different version that have 52, 101, 152 layers respectively.

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